AD-A048 004 CENTER FOR NAVAL ANALYSES ARLINGTON VA MARINE CORPS --ETC F/G 5/9
A METHODOLOGY FOR COMPARISON OF ATTRITION FORECASTING MODELS,(U)
JUL 77 C A MILLARD
N00014-76-C-0001

UNCLASSIFIED CRC-318 NL

1 OF 1
ADA048 004

END
DATE
FILMED
1-78
DDC

CRC 318

(12)

A METHODOLOGY FOR COMPARISON OF ATTRITION FORECASTING MODELS

AD A048004

CENTER FOR NAVAL ANALYSES
1401 Wilson Boulevard
Arlington, Virginia 22209

Marine Corps Operations Analysis Group

By: Charles A. Millard, Capt., USMC

July 1977

Prepared for:

OFFICE OF NAVAL RESEARCH
Department of the Navy
Arlington, Virginia 22217

DEPUTY CHIEF OF STAFF (RD&S)
Headquarters, Marine Corps
Washington, D.C. 20380

02 031800.00

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER CRC-318	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) A Methodology for Comparison of Attrition Forecasting Models		5. TYPE OF REPORT & PERIOD COVERED
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Charles A. Millard, Capt., USMC		8. CONTRACT OR GRANT NUMBER(s) N00014-76-C-0001
9. PERFORMING ORGANIZATION NAME AND ADDRESS Center for Naval Analyses 1401 Wilson Boulevard Arlington, Virginia 22209		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 46p.
11. CONTROLLING OFFICE NAME AND ADDRESS Deputy Chief of Staff (RD&S) Headquarters, Marine Corps Washington, D.C. 20380		12. REPORT DATE July 1977
		13. NUMBER OF PAGES 38
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

This Research Contribution does not necessarily represent the opinion of the Commandant, Headquarters, Marine Corps.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

attrition, chi-square, enlisted personnel, forecast, linear systems, Marine Corps personnel, models, predictions, recruiting, regression analysis, retention (general)

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This analysis develops a methodology for comparing forecasting models and examines in detail the ability of available attrition/success models to adequately predict the service performance of nongraduate Marines. Available models will almost always select graduates over nongraduates; therefore, it is possible that these models cannot optimally select from among the remaining nongraduates -- some of whom the Marine Corps will be forced to accept. The data was disaggregated and the attrition of graduates and nongraduates was examined separately. The results of this analysis indicate that using a separate attrition/success model developed especially for non-

DD FORM 1473 1 JAN 73 EDITION OF 1 NOV 65 IS OBSOLETE

S/N 0102-LF-014-6601

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

401 327

20 graduates will not significantly improve the accuracy and reliability of prediction. The conclusion, therefore, is that existing models, which deal with an aggregated population, are both appropriate and sufficient.

Center
for
Naval
Analyses

1401 Wilson Boulevard Arlington, Virginia 22209 703/524-9400

An Equal Opportunity Employer

an affiliate of the
University of Rochester

31 October 1977

MEMORANDUM FOR DISTRIBUTION LIST

Subj: Center for Naval Analyses Research Contribution 318

Encl: (1) CRC 318, "A Methodology for Comparison of Attrition Forecasting Models," by Capt. Charles A. Millard, USMC July 1977

1. Enclosure (1) is forwarded as a matter of possible interest.

2. This Research Contribution develops a technique for comparing the relative accuracy and utility of linear forecasting models. It then applies the technique to forecasts of personnel attrition (premature discharge and desertion) to determine whether high school graduates and nongraduates require separate attrition models. The results may be useful to planners whose sources of information include more than one forecasting model and particularly to manpower planners concerned with personnel attrition.

3. Research Contributions are distributed for their potential value in other studies and analyses. They do not necessarily represent the opinion of the U.S. Marine Corps or the Department of the Navy.

Robert J. C

ROBERT J. CORN
Director
Marine Corps Operations
Analysis Group

Subj: Center for Naval Analyses Research Contribution 318

DISTRIBUTION LIST

Department of the Navy

SNDL Part I:

21A1	CINCLANTFLT
21A2	CINCPACFLT
21A3	CINCUSNAVEUR
22A1	COMSECONDFLT
22A2	COMTHIRDFLT
22A2	COMSEVENTHFLT
22A3	COMSIXTHFLT
24H1	COMTRALANT
24H2	COMTRAPAC
24J1	CG FMFLANT
24J2	CG FMFPAC
45B	CG FIRST MARDIV
45B	CG SECOND MARDIV
45B	CG THIRD MARDIV
45B	CG FOURTH MARDIV
46B	CG FIRST MAW
46B	CG SECOND MAW
46B	CG THIRD MAW

SNDL Part II:

A1	ASST SECNAV (FM)
A1	ASST SECNAV (M&RA)
A2A	NAVCOMPT
A2A	OPA
A2A	ONR
A5	CHNAVPERS
A6	DC/S, Manpower (10)
A6	DC/S, P&P
A6	DC/S, RD&S (2)
A6	DC/S, R&P
A6	DC/S, O&T
A6	Fiscal Dir, USMC
B3	NAT'L DEF UNIV
B3	AFSC
FA34	HUMRESMANCEN LANT
FB44	HUMRESMANCEN San Diego
FB44	HUMRESMANCEN Pearl Harbor
FC9	HUMRESMANCEN London
FF30	NAVMMACLANT
FF30	NAVMMACPAC
FF38	USNA, Nimitz Library
FF48	HUMRESMANCEN
FJ18	NAVPERSPROGSUPPACT
FJ76	COMNAVCRUITCOM
FKA6A16	NAVPERSRANDCEN
FT1	CNET
FT2	CNATRA
FT5	CNTECHTRA
FT73	NAVPGSCOL
FT75	NAVWARCOL
FT87	HUMRESMANSCOL
V8	MARCORCRUITDEP Paris Island
V8	MARCORCRUITDEP San Diego
V12	CG MCDEC
OpNav:	Op-09BH
	Op-90
	Op-099
	Op-01
	Op-10
	Op-12

Other

Director, Defense Research and Engineering
Ass't SecDef, Program Analysis & Evaluation (2)
Ass't SecDef, Manpower & Reserve Affairs
Defense Documentation Center (12)
Department of the Army (Adj Gen'l)(6)
Department of the Air Force (AFXOD)
Institute for Defense Analyses
Human Resource Research Organization
The Rand Corporation

TABLE OF CONTENTS

I. INTRODUCTION

BACKGROUND

Current Marine Corps recruiting policies show a strong preference for high school graduates. These policies are the result of analytic evidence that the educational level of a recruit is highly correlated with the quality of his later military service. More specifically, high school graduates have been shown to have higher promotion rates and lower attrition rates. Thus, by biasing its recruiting to increase the ratio of high school graduates to nongraduates, the Marine Corps can improve the average quality of service of its members and can reduce personnel turbulence resulting from discharge and desertion. Effectively implementing such policies is essential if the Marine Corps is to successfully compete for recruits in the environment of an All-Volunteer Force. Evidence suggesting that the number of potential recruits is declining as a result of fluctuations in U.S. birthrates makes effective implementation of these policies even more important.

Literature is available that provides lists of variables to be used to predict quality of performance or success of service, when applied to the total population of potential recruits. Reference 1, for example, presents a method to predict success in the Marine Corps as a function of education, age, and the Army Classification Battery (ACB-61) test scores for Classification Inventory (CI) and the General Classification Test (GCT). That model is predicated on the generally accepted assumption that the realities of supply and demand will force the Marine Corps to continue to accept a certain number of recruits who are not high school graduates. It, therefore, includes educational level as a variable. But once the initial question of educational level has been answered, what factors should be used for subsequent screening? Are they the same for graduates and nongraduates? Clearly, while graduates are generally preferred, not all graduates should be accepted. Neither should all nongraduates be rejected. If it is true that a high school graduate accession rate of 100 percent is impossible, then the Marine Corps must have the tools with which to select potential recruits from the two population sub-groups. It is unclear whether such tools are currently available. Apparently, the questions posed above concerning separate screening factors for graduates and non-graduates have never been answered.

OBJECTIVES

Given the extreme pressures of recruiting, it is important to maximize the accuracy and usefulness of the model on which recruiting policies are based. This analysis examines the question of whether forecasts of quality and success can be improved by treating high school graduates and nongraduates separately. More specifically, the objectives are as follows:

- To develop a (disaggregated) model for separately predicting the success of high school graduates and nongraduates,
- To determine whether there is a statistically significant difference between that disaggregated model and the aggregated model of reference 1, and
- If the observed differences are significant, to determine which model provides the better basis for recruiting policy.

The methodology developed for comparing the two models will be applied to the specific questions iterated above, but is applicable in a much broader sense -- i.e., to forecasting models in general. One can normally find several predictions, or forecasts, of future conditions. A precise understanding of the nature of the forecasts, and the differences between them, is therefore of potential importance.

FINDINGS

This analysis indicates that attrition/success estimates based on an aggregated model are, in fact, different from those based on a disaggregated model. The aggregated model treats all potential recruits as members of a single homogeneous population. The disaggregated model separates, or disaggregates, the high school graduates and nongraduates and examines them as separate and distinct subgroups. The analysis further demonstrates that although the observed differences are statistically significant at the 95-percent confidence level, they are relevant only in a purely theoretical sense. In a realistic recruiting application, the differences in the predicted attrition rates of the two alternative models are not operationally important. The aggregated model is, therefore, appropriate and sufficient as a basis for recruiting policy. Since it is also the simpler of the two models, it is the preferred alternative.

Although the precise use of any such model is a matter for Marine Corps decision makers, one point worthy of note is evident from this analysis. A regression model, properly applied as an enlistment screening device, can effectively enlarge the pool of potential recruits. When considered in the context of increasingly competitive and difficult recruiting, that point is significant.

II. DATA AND METHODOLOGY

DATA

The data for this analysis is the same as was used in reference 1. It consists of personal characteristics, test scores, and 2-year attrition statistics collected from the records of approximately 46,000 regular, male, nonprior-service enlistees who reported for recruit training during FY 1974. These records were obtained from the Manpower Management System (MMS) and the Recruit Accession Management System (RAMS).

Variables

The personal characteristics chosen for this analysis are age, race, and marital status. In order to be consistent with previous work in this area, all three are assumed to be dichotomous variables. Age (upon reporting for active duty) is either 17-20 or 21 and over, race is either white or nonwhite, and marital status (upon reporting) is either married or unmarried.

The test scores are from the 11 ACB-61 subtests administered to each enlistee upon arrival at the recruit depot. Even though the Armed Services Vocational Aptitude Battery (ASVAB) has supplanted the ACB-61, it was necessary to use ACB-61 data in this analysis. The ASVAB was not used until 1975, so performance data for recruits to whom it was given is limited.[1] Using ACB-61 data should not detract from the results, however. The objective of this analysis is not to generate specific values of the prediction variable but, rather, to determine whether a disaggregated model is required and, if so, how such a model might be developed. These questions can be answered on the basis of ACB-61 data and the results later generalized to ASVAB data, if necessary.

A variable for enlistment guarantees was also included in the analysis. Since such guarantees are used to induce enlistment, they were included to determine what effect, if any, they have on service after enlistment.

Although success is the variable of primary interest, its major determinants are attrition (desertion and premature discharge) and promotion. Since attrition is also of interest in its own right, it has been chosen as a surrogate for success and is the dependent variable for this analysis. Success, then, is indicated by the ability to remain in service for at least 2 years following enlistment. This choice has the advantages of simplicity and clarity and facilitates comparisons with reference 1, which likewise used attrition as a measure of success.

---

[1] Reference 2 has taken a preliminary look at the service performance of a 2-month cohort of recruits who were administered the ASVAB tests. The results of that analysis will be commented upon later.

Table 1 lists the explanatory variables and their possible values.

TABLE 1

VARIABLES

Dependent variable	Value
Attrition	0 = Neither desertion nor early attrition 1 = Either one or both
Independent/explanatory variables	
Age	0 = 17-20 1 = 21 or more
Race	1 = White 2 = Nonwhite
Marital status	0 = Unmarried 1 = Married
Enlistment guarantee	0 = None 1 = Cash 2 = Noncash
ACB-61 test scores VE (Verbal) AR (Arithmetic) PA (Pattern Analysis) CI (Classification Inventory) MA (Mechanical Aptitude) ACS (Army Coding Speed) ARC (Army Radio Code) GIT (General Information) SM (Shop Information) AI (Automotive Information) ELI (Electronics Information)	Standard score
ACB-61 composite GCT (General Classification Test)	1/3(VE + AR + PA)

METHODOLOGY

The method of analysis is step-wise multiple linear regression of the explanatory (independent) variables on attrition (the dependent variable). This technique makes it possible to construct a linear model that will predict attrition (success) as a function of specified values of the explanatory variables. The step-wise approach also identifies the relative importance of the explanatory variables in predicting attrition. This approach allows a user of the model to greatly simplify its form by eliminating (ignoring) the variables that contribute little to its predictive ability.

The regression is applied to disaggregated subsets of the data base: one containing high school graduates only, the other nongraduates only.[1] A set of equations to predict success in the Marine Corps is presented. This model, which differentiates between high school graduates and nongraduates, is compared with the aggregated model of reference 1. Observations are made concerning the applicability of the models to potential Marine Corps uses.

---

[1] Individuals with a High School General Equivalency Diploma (GED) were included in the nongraduate subgroup because evidence suggests that they tend to behave more like nongraduates than graduates in their service performance (reference 3).

III. RESULTS

For this analysis, the regression technique was manipulated to produce the following information:

- Means and standard deviations for each variable;
- Coefficients of correlation between each variable and every other variable; and
- Regression statistics for five different combinations of variables.

The results of these manipulations are shown in appendixes A and B.

Table 2 shows the means and standard deviations of each variable for both high school graduates and nongraduates (95-percent confidence intervals are contained in appendix A -- as are the coefficients of correlation between every possible pair of variables). Note that, compared to nongraduates, high school graduates are generally older, less likely to fall prey to attrition, and more likely to be white and single. They also have consistently higher scores on the ACB-61 subtests.

The primary output of a regression analysis is an equation that can be used to predict values of a dependent variable (such as attrition), based on specified or observed values of one or more independent variable (such as GCT score). The coefficients of the independent variables in the regression equation indicate their relative importance in predicting values of the dependent variable. Their sign indicates the direction of the effect. A negative coefficient, for example, predicts decreasing values of the dependent variable for increasing values of the independent variable.

The quality of the regression equation is indicated by the R^2 and F statistics. The R^2 statistic measures the proportion of total variation in the dependent variable that is explained by the independent variables. The partial F statistic measures the significance of a given independent variable as a predictor for the dependent variable.

The step-wise procedure used in this analysis selects variables in decreasing order of their contribution to minimizing residual variation. The first variable selected as a predictor explains more of the total variation in the dependent variable than any other single variable. The next variable contributes more to explaining the residual (remaining) variation than any other remaining variable. This step-wise procedure continues until the independent variables are exhausted. Normally, some residual variation remains at the completion of the regression, since a perfect prediction model is seldom available. Therefore, the value of R^2 will always be less than 1. It will, in fact, be between 0 and 1 in any application of the regression technique to actual (uncontrived) data.

TABLE 2

MEANS AND STANDARD DEVIATIONS

Variables	Graduates Mean	Graduates Std.Dev.	Nongraduates Mean	Nongraduates Std.Dev.
Attrition	0.20	0.40	0.45	0.50
Age	0.12	0.33	0.08	0.27
Race	1.20	0.40	1.24	0.43
Marital status	1.06	0.25	1.08	0.27
VE	108.24	22.22	92.62	20.98
AR	103.43	22.26	88.63	19.96
PA	110.96	21.48	100.38	22.00
CI	102.49	26.45	89.99	27.23
MA	104.34	20.16	94.56	18.21
ACS	103.00	19.76	92.47	19.49
ARC	90.06	26.50	77.89	23.80
GIT	99.41	19.84	87.43	18.52
SM	101.10	18.90	91.67	17.97
AI	102.46	19.53	95.75	18.46
ELI	97.47	23.92	88.07	22.45
GCT	107.54	19.56	93.88	18.05

DEVELOPING THE DISAGGREGATED MODEL

To identify the variables that most accurately and conveniently predict attrition, the regression technique was applied to five combinations of variables. Since the data base has been disaggregated into two subgroups -- graduates and nongraduates -- ten separate regression relationships are produced. The results, shown in appendix B, are regression numbers HS-1 through HS-5 for high school graduates and NG-1 through NG-5 for nongraduates.

The complete set of explanatory variables was examined first, producing regression numbers HS-1 and NG-1. Since, ultimately, it is desirable to have a regression model that is not only as accurate and powerful as possible, but also as simple and useful as possible, the number of variables was limited on the basis of their relative contribution to explaining the variation in the observed attrition, as demonstrated in HS-1 and NG-1. An examination of the "R^2" and "CUMULATIVE R^2" columns of table 3 (or appendix B) reveals that in terms of their relative contributions to cumulative R^2, two or three variables would probably be sufficient for the model. Beyond that point, the marginal contribution to explaining residual variation is small. The three best predictor variables for the two population subgroups are:

Graduates	Nongraduates
PA	CI
AGE	PA
CI	GUAR

GUAR was eliminated from consideration for the model because it is not considered a valid enlistment screening device. Enlistment guarantee is used during the recruiting process as an inducement to deserving and reluctant prospects. It does not, however, affect the eligibility of the applicant and is therefore not legitimately involved in the initial screening process. Additionally, GCT was substituted for PA, since it includes PA and is already widely known and used as an indicator of quality. The loss in cumulative R^2 that results from the substitution is very small (viz., 0.00027 for graduates and 0.00031 for nongraduates). The loss is more than justified by using a variable that has wide application in both recruiting and school assignment. Reference 4, for example, demonstrates that GCT is an excellent predictor of school performance. GCT has the additional convenience of being highly correlated with the Mental Group (MG) composite of the ASVAB, which is currently used.

Thus, the second pair of regressions (HS-2 and NG-2) involved GCT, CI, and AGE. The third, fourth, and fifth regressions merely tested different combinations of the variables, such as test scores only and personal characteristics only. The results are shown in tables B-1 and B-2 of appendix B.

TABLE 3

RESULTS OF VARIABLE GROUPINGS

	Graduates				Nongraduates		
No.	Var	ΔR^2	Cum R^2	No.	Var	ΔR^2	Cum R^2
HS-1	PA	0.0311	0.0311	NG-1	CI	0.0300	0.0300
	AGE	0.0104	0.0415		PA	0.0115	0.0415
	CI	0.0109	0.0424		GUAR	0.0024	0.0439
	GUAR	0.0039	0.0563		AGE	0.0012	0.0451
	GIT	0.0020	0.0583		GIT	0.0011	0.0462
	VE	0.0005	0.0588		RACE	0.0006	0.0468
	AR	0.0009	0.0597		AR	0.0005	0.0473
	RACE	0.0004	0.0603		VE	0.0003	0.0476
	ARC	0.0004	0.0607		MARIT	0.0003	0.0479
	MARIT	0.0003	0.0610		MA	0.0003	0.0482
	ELI	0.0002	0.0612		SM	0.0001	0.0483
	SM	0.0000	0.0612		ARC	0.0001	0.0484
	ACS	0.0000	0.0612		ACS	0.0001	0.0485
	AI	0.0000	0.0612		ELI	0.0001	0.0486
	MA	0.0000	0.0612		AI	0.0000	0.0486
HS-2	GCT	0.0336	0.0336	NG-2	GCT	0.0339	0.0339
	AGE	0.0116	0.0452		CI	0.0072	0.0411
	CI	0.0069	0.0521		AGE	0.0025	0.0436
HS-3	PA	0.0311	0.0311	NG-3	CI	0.0300	0.0300
	CI	0.0100	0.0411		PA	0.0115	0.0415
	GIT	0.0022	0.0433		AR	0.0015	0.0430
	ARC	0.0005	0.0438		GIT	0.0007	0.0437
	VE	0.0006	0.0444		MA	0.0003	0.0440
	AR	0.0008	0.0452		VE	0.0002	0.0442
	ELI	0.0002	0.0454		ARC	0.0001	0.0443
	SM	0.0001	0.0455		ACS	0.0001	0.0444
	ACS	0.0000	0.0455		SM	0.0001	0.0445
	AI	0.0000	0.0455		ELI	0.0000	0.0445
	MA	0.0000	0.0455		AI	0.0000	0.0445
HS-4	GCT	0.0336	0.0336	NG-4	GCT	0.0339	0.0339
	CI	0.0064	0.0400		CI	0.0073	0.0412
	GUAR	0.0043	0.0443		GUAR	0.0017	0.0429
HS-5	AGE	0.0128	0.0128	NG-5	RACE	0.0031	0.0031
	RACE	0.0070	0.0198		AGE	0.0016	0.0047
	MARIT	0.0002	0.0200		MARIT	0.0004	0.0051

The three variables GCT, CI, and AGE are seen to explain more of the variation in observed attrition than any other combination of variables tested, except the complete set. The loss in explained variation (R^2), resulting from the reduction from 15 to 3 variables, is very small (on the order of 1/2 to 1 percent) and is more than offset by the gain in simplicity and potential usefulness. The F-ratios for the three variables are large enough to indicate with 99-percent certainty that they appear in the regression equation because of true statistical association with attrition and not by chance. Thus, the attrition model selected is a linear combination of the GCT, CI, and AGE variables.

Before proceeding, it should be noted that test scores are clearly superior to personal characteristics as predictors of attrition. Therefore, testing of enlistment candidates is of paramount importance if successful screening -- and effective recruiting -- is to be accomplished. It remains true, however, that combinations of test scores and personal characteristics (viz., GCT, CI, and AGE) provide the best available basis for an enlistment screening model.

TWO ATTRITION MODELS

We now have two consistent, but slightly different, models for predicting attrition: the aggregated model of reference 1 and the disaggregated model developed herein. These two models may be represented as:

- AGGREGATED MODEL

$$A_{AG} = 0.8694 + 0.1090\,(AGE) - 0.0029\,(GCT) - 0.0017\,(CI) - 0.1870\,(ED)$$

- DISAGGREGATED MODEL

$$A_{HS} = 0.6150 + 0.1341\,(AGE) - 0.0025\,(GCT) - 0.0015\,(CI)$$

and

$$A_{NG} = 0.9333 + 0.0714\,(AGE) - 0.0034\,(GCT) - 0.0019\,(CI)\,,$$

where

A = probability of attrition,

AG = the aggregated model,

HS = high school graduate,

NG = nongraduate, and

ED = a dichotomous variable for educational level (i.e., ED = 1 for a high school graduate and ED = 0 for a nongraduate).

Tables 4 through 7 show the attrition rates predicted by the disaggregated model. Similar tables for the aggregated model are contained in reference 1.

TABLE 4

PREDICTED ATTRITION RATES:
HIGH SCHOOL GRADUATES, AGES 17-20

		GCT 120	110	100	90	80	70	60
	120	0.135	0.160	0.185	0.210	0.235	0.260	0.285
	110	0.150	0.175	0.200	0.225	0.250	0.275	0.300
	100	0.165	0.190	0.215	0.240	0.265	0.290	0.315
CI	90	0.180	0.205	0.230	0.255	0.280	0.305	0.330
	80	0.195	0.220	0.245	0.270	0.295	0.320	0.345
	70	0.210	0.235	0.260	0.285	0.310	0.335	0.360
	60	0.225	0.250	0.275	0.300	0.325	0.350	0.375

Attrition = 0.6150 - 0.0025(GCT) - 0.0015(CI)

TABLE 5

PREDICTED ATTRITION RATES:
HIGH SCHOOL GRADUATES, AGES 21 AND OVER

		GCT 120	110	100	90	80	70	60
	120	0.269	0.294	0.319	0.344	0.369	0.394	0.419
	110	0.284	0.309	0.334	0.359	0.384	0.409	0.434
	100	0.299	0.324	0.349	0.374	0.399	0.424	0.449
CI	90	0.314	0.339	0.364	0.389	0.414	0.439	0.464
	80	0.329	0.354	0.379	0.404	0.429	0.454	0.479
	70	0.344	0.369	0.394	0.419	0.444	0.469	0.494
	60	0.359	0.384	0.409	0.434	0.459	0.484	0.509

Attrition = 0.7491 - 0.0025(GCT) - 0.0015(CI)

TABLE 6

PREDICTED ATTRITION RATES;
NONGRADUATES, AGE 17-20

GCT

		120	110	100	90	80	70	60
	120	0.297	0.331	0.365	0.399	0.433	0.478	0.501
	110	0.316	0.350	0.384	0.418	0.452	0.486	0.520
	100	0.335	0.369	0.403	0.437	0.471	0.505	0.539
CI	90	0.354	0.388	0.422	0.456	0.490	0.524	0.558
	80	0.373	0.407	0.441	0.475	0.509	0.543	0.577
	70	0.392	0.426	0.460	0.494	0.528	0.562	0.596
	60	0.411	0.445	0.479	0.513	0.547	0.581	0.615

Attrition = 0.9333 - 0.0034(GCT) - 0.0019(CI)

TABLE 7

PREDICTED ATTRITION RATES: NONGRADUATES,
AGE 21 AND OVER

GCT

		120	110	100	90	80	70	60
	120	0.369	0.403	0.437	0.471	0.505	0.539	0.573
	110	0.388	0.422	0.456	0.490	0.524	0.558	0.592
	100	0.407	0.441	0.475	0.509	0.543	0.517	0.611
CI	90	0.426	0.460	0.494	0.528	0.562	0.596	0.630
	80	0.445	0.479	0.513	0.547	0.581	0.615	0.649
	70	0.464	0.498	0.532	0.566	0.600	0.634	0.668
	60	0.483	0.517	.0551	0.585	0.619	0.653	0.687

Attrition = 1.0047 - 0.0034(GCT) - 0.0019(CI)

COMPARING THE MODELS

Having constructed two models for generating estimates of the same variable (attrition), it is now necessary to determine whether the differences are statistically significant at a given level and, if so, to quantify and interpret them. The first part of this comparison requires an hypothesis test in which the null hypothesis is that there is no difference between the two models. The hypothesis test uses a variation of the mean square error test for exact linear restriction in regression (reference 5). A statistic u is distributed as the noncentral F with m and n degrees of freedom:

$$u = \frac{SSE(B) - SSE(b)}{m} \div \frac{SSE(b)}{n} ,$$

where SSE(B) = the calculated error sum of squares in the restricted regression, and SSE(b) = the calculated error sum of squares in the unrestricted regression. The mean square error test is essentially a test of the significance of the (mean square) error introduced by constraining the regression to linearity in a specified number of variables. It is frequently used to test an hypothesis of linearity. The variation used in this hypothesis test measures the significance of the differences between the errors introduced by the two sets of constraint variables. It may be expressed as:

$$F = \frac{SSE(A) - SSE(D)}{m} \div \frac{SSE(D)}{n} ,$$

where SSE(A) = Error sum of squares in the regression of the aggregated model,

SSE(D) = Error sum of squares in the regression of the disaggregated model (equal to the sum of the error sums of squares of the high school graduate and nongraduate portions of the model),

m = number of variables in the regression,

and n = number of observations (sample size).

This equation yields an F statistic with a value of F = 11.9. Since this is greater than $F_{.95}(3, \infty) = 2.60$, we reject the null hypothesis and conclude that the observed differences between the two models are significant at the 95-percent confidence level.

To quantify the differences between the models, an approach patterned after that in reference 6 was adopted. The attrition models are assumed to be enlistment screening devices that determine whether a potential enlistee is accepted. For each potential enlistee, the models produce an estimate of probable attrition, based on his educational status, age, and test scores (GCT and CI). Such an enlistee would then be accepted if his probable attrition were less than some maximum acceptable level specified by higher headquarters. Otherwise, he would be rejected. This use of the model parallels

the U.S. Navy practice of computing SCREEN[1] scores. For the sake of convenience, we designate the output of each model as the individual's CAREM[2] score.

Each of the approximately 46,000 individuals in the data base has a unique CAREM score because each has a unique set of personal characteristics and test scores. These individuals can, therefore, be grouped according to whether the models, if used as enlistment screening devices, would have admitted or rejected them for a given CAREM cutting score. They can further be subgrouped by whether they stayed for 2 years following enlistment or were subject to attrition. Tables 8 and 9 show the following:

- Correct predictions by the models

  - Correct acceptances: The number of persons who would have been accepted by the model and who actually stayed in service the required 2 years.

  - Correct rejections: The number of persons who would have been rejected by the model and who actually did not stay for 2 years.

- Incorrect predictions by the models

  - Incorrect acceptances: The number of persons who would have been accepted by the model, but who did not stay in service for 2 years.

  - Incorrect rejections: The number of persons who would have been rejected by the model, but who actually stayed for 2 years.

For every specified value of the CAREM cutting score, the disaggregated model can be seen to be superior to the aggregated model, if only slightly so. For example, at a cutting score of 0.50, the aggregated model would have been correct 68.2 percent of the time had it been applied as an enlistment criterion to the individuals in the data base (see table 9). The comparable figure for the disaggregated model is slightly better at 68.3 percent.

The ability of these two models to correctly accept and reject potential enlistees can be compared by using the Chi-Square test illustrated in appendix C. The null hypothesis for the comparisons is that the number of applicants accepted and/or rejected is independent of the choice of models -- i.e., that they are essentially identical.

---

[1]SCREEN is an acronym for Success Chances for Recruits Entering the Navy.

[2]CAREM is an acronym for Chances of Attrition for Recruits Entering the Marines.

TABLE 8

NUMBERS OF CORRECT AND INCORRECT PREDICTIONS

Aggregated model

Cutting score	.50	.45	.40	.35	.30	.25	.20
Correct acceptances	27,422	24,540	20,935	17,252	14,460	11,717	8,042
Incorrect acceptances	11,651	9,106	6,583	4,484	3,213	2,219	1,324
Correct rejections	4,026	6,571	9,094	11,193	12,464	13,458	14,353
Incorrect rejections	2,986	5,868	9,473	13,156	15,948	18,691	22,366
Total correct	31,448	31,111	30,029	28,445	26,924	25,175	22,395
Total incorrect	14,637	14,974	16,056	17,640	19,161	20,910	23,690

Disaggregated model

Cutting score	.50	.45	.40	.35	.30	.25	.20
Correct acceptances	27,342	24,706	21,477	18,147	15,133	12,229	8,343
Incorrect acceptances	11,525	9,241	6,957	4,934	3,456	2,353	1,377
Correct rejections	4,152	6,436	8,720	10,743	12,221	13,324	14,300
Incorrect rejections	3,066	5,702	8,931	12,261	15,275	18,179	22,065
Total correct	31,494	31,142	30,197	28,890	27,354	25,553	22,643
Total incorrect	14,591	14,943	15,888	17,195	18,731	20,532	23,442
Chi-square (χ^2):	3.80	5.34	41.07	84.88	41.06	22.66	8.71

TABLE 9

PERCENTAGE OF CORRECT AND INCORRECT PREDICTIONS

Aggregated model

Cutting score	.50	.45	.40	.35	.30	.25	.20
Correct acceptances	59.5	53.2	45.4	37.4	31.4	25.4	17.5
Incorrect acceptances	25.3	19.8	14.3	9.7	7.0	4.8	2.9
Correct rejections	8.7	14.3	19.7	24.3	27.0	29.2	31.1
Incorrect rejections	6.5	12.7	20.6	28.5	34.6	40.6	48.5
Total correct	68.2	67.5	65.1	61.7	58.4	54.6	48.6
Total incorrect	31.8	32.5	34.9	38.2	41.6	45.4	51.4

Disaggregated model

Cutting socre	.50	.45	.40	.35	.30	.25	.20
Correct acceptances	59.3	53.6	46.6	39.4	32.8	26.5	18.1
Incorrect acceptances	25.0	20.1	15.1	10.7	7.5	5.1	3.0
Correct rejections	9.0	14.0	18.9	23.3	26.5	28.9	31.0
Incorrect rejections	6.7	12.4	19.4	26.6	33.1	39.4	47.9
Total correct	68.3	67.6	65.5	62.7	59.3	55.4	49.1
Total incorrect	31.7	32.5	34.5	37.3	40.6	44.5	50.9

The Chi-Square values for each of the seven CAREM cutting scores, calculated by the procedures of appendix C, are shown at the bottom of table 8. Since the critical Chi-Square value (for 95-percent confidence and 3 degrees of freedom) is 7.8, the null hypothesis can be rejected for CAREM cutting scores of 0.40 and below -- indicating that the models produce different results in this range. For scores of 0.45 and 0.50, however, the results do not appear to be significantly different for the two models.

By varying the cutting scores, one can simultaneously affect both the number of people the screening model will accept and the attrition probability of those accepted. These effects are shown in figures 1 and 2 and are combined in figure 3, which shows the relationship between attrition and the size of the potential recruit pool. These figures demonstrate that by reducing the cutting score, one can reduce the probability of attrition for those entering the service, but only at the cost of a significant reduction in the number of people eligible for enlistment. These effects can best be quantified by the elasticities of eligibility and attrition with respect to cutting score.

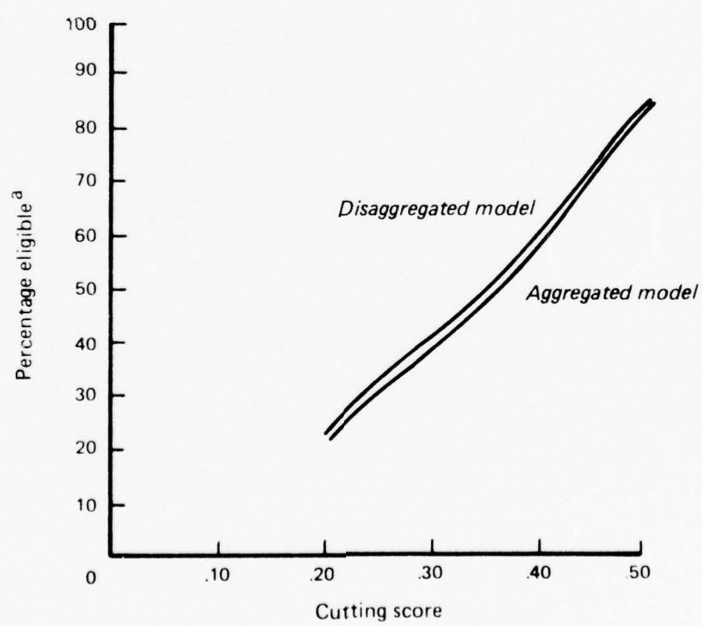

FIG. 1: EFFECT OF CUTTING SCORES ON THE SIZE OF THE ELIGIBLE POPULATION[a]

[a] *The percentage of eligibles is measured by the proportion of total acceptances (both correct and incorrect) by the screening model.*

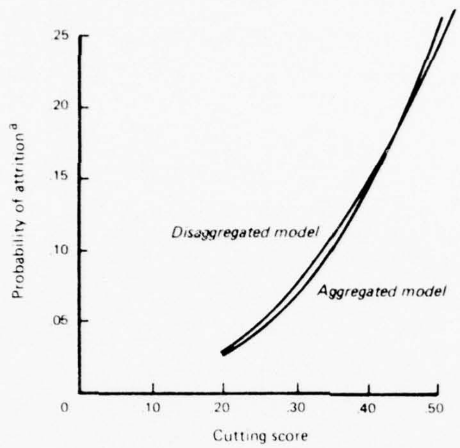

FIG. 2: EFFECT OF CUTTING SCORES ON THE PROBABILITY OF ATTRITION[a]

[a] *The probability of attrition is measured by the proportion of incorrect acceptances by the screening model.*

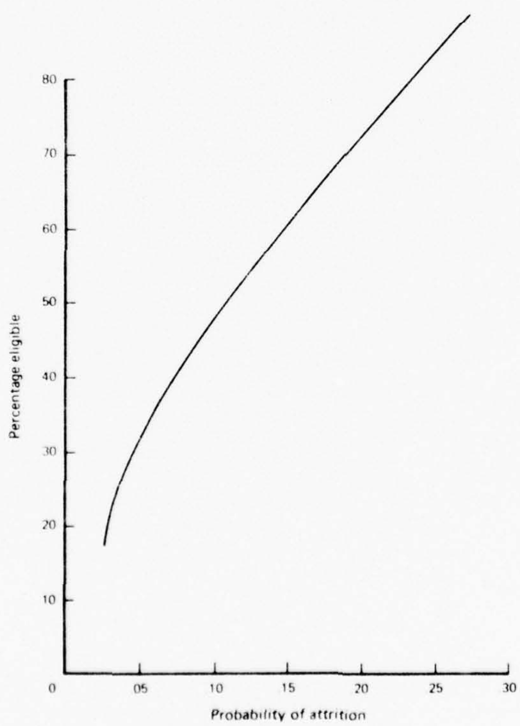

FIG. 3: RELATIONSHIP BETWEEN PROBABILITY OF ATTRITION AND SIZE OF ELIGIBLE POPULATION

Elasticity is an expression of the amount of change in a dependent variable that results from a given change in an independent variable -- at a given value of the independent variable. For two variables related by the expression $Y = f(X)$, the elasticity of Y with respect to X at $X = X_1$ may be defined as:

$$e = \frac{\dfrac{Y_2 - Y_1}{Y_1}}{\dfrac{X_2 - X_1}{X_1}} .$$

At a cutting score of 0.45, the elasticity of attrition is 2.3, while that of eligibility is 1.4. As a result, for a one-percent reduction in cutting score, one can achieve a 2.3-percent reduction in attrition, but only at the expense of a 1.4-percent reduction in eligibility. It should also be noted that elasticities are not constant throughout the range of the variables. They apply only to values in the immediate vicinity of the point at which calculated. The cutting score of 0.45 was deliberately chosen as the point at which to calculate the elasticities because it appears to be in the vicinity of values most relevant to realistic and effective recruiting.

Given the significant impact of reductions in cutting score on the size of the eligible population, there appears to be a limit to the amount of attrition one can realistically hope to eliminate. Since cutting scores above 0.45 would deny enlistment to nearly one out of every three potential recruits (figure 1), reductions below this point are undoubtedly inconsistent with successful recruiting efforts. At the same time, it is undesirable to allow individual attrition probabilities greater than about 0.50. We are therefore restricted to a practical range of cutting scores from 0.40 to 0.50. This range of values presents a dilemma, however. The F-test indicated that the differences between the two models were statistically significant for all values of the cutting score, while the Chi-Square test indicated significance only for values less than 0.45. Given this apparent contradiction, one is forced to conclude that these standard comparison tests do little more than indicate that the models are "almost, but not quite" different (or the same) in terms of what they predict.

A common-sense approach to this dilemma leads one to compare the models on the basis of their performance in a hypothetical recruiting application. Assuming that the average annual recruit accession goal of the Marine Corps is 50,000 recruits, the number of mistakes (incorrect decisions) that would be made by each model is shown in table 10 for two realistic values of a possible CAREM cutting score.

TABLE 10

ATTRITION MODEL PERFORMANCE

	Aggregated model (A)		Disaggregated model (D)		Difference (A-D)	
Cutting score	0.50	0.45	0.50	0.45	0.50	0.45
Incorrect acceptances	12,641	9,880	12,504	10,026	137	-146
Incorrect rejections	3,240	6,366	3,326	6,186	- 86	180
Total	15,881	16,246	15,830	16,212	51	34

The disaggregated model would apparently reject 86 more potentially successful Marines than would the aggregated model at CAREM = 0.50. This involves an indeterminate, but very real, recruiting cost. At the same CAREM level, however, the disaggregated model would also accept fewer failures, resulting in a savings in training costs, pay, and turbulence (discharges, etc.). The degree to which these potential costs and savings would offset each other is not known; but, overall, the disaggregated model would make approximately 50 fewer "mistakes" per year than would the aggregated model. Thus, in practical terms, the difference is less than one mistake per week. At a cutting score of CAREM = 0.45, the exact figures are slightly different, but the final result is essentially the same. It is not considered realistic to ascribe any practical significance to such a small difference.

It should be noted at this point that establishing the cutting score at CAREM = 0.45 does not imply a net attrition rate of 45 percent. It simply eliminates from eligibility all individuals with a probability of attrition of 0.45 or greater. Eliminating those individuals drastically alters the attrition probability distribution of the remaining eligible population so that the expected Corps-wide attrition would actually be about 20 percent, as illustrated in figure 2. Such an attrition rate is consistent with current Marine Corps goals.

IV. SUMMARY AND CONCLUSIONS

The fact that high school graduates perform better than nongraduates in Marine Corps service has been amply demonstrated by numerous analyses. In fact, the education variable so dominates every existing prediction model that a real danger exists that, once its influence is eliminated, a new and different set of predictor variables might emerge. A separate examination of high school graduates and nongraduates has produced an attrition model that differs from the model in reference 1, which treats graduates and nongraduates as a single aggregated population. The two models contain the same variables, but the relative importance of the variables is different. The two models therefore produce different results in terms of the attrition they predict. They also produce different results when applied as enlistment screening devices. The differences, however, have no practical significance. The relative advantages that might accrue from selecting one model over the other are negligible.

It is therefore concluded that there is no advantage to be gained from applying different enlistment eligibility criteria for high school graduates and nongraduates. There is no justification for using the relatively more complicated dual (disaggregated) model. A model patterned after that in reference 1 is sufficient. Although these conclusions are based on an analysis of data containing ACB-61 scores, there is no reason to suspect that they would change if the analysis were applied to ASVAB data. The underlying principles are the same in either case. The results are, in fact, consistent with those reported in reference 2, which is based on a preliminary examination of ASVAB data.

With regard to the actual use of an enlistment screening (CAREM) model in a recruiting application, it should be noted that such use could allow the weaknesses of a potential recruit to be partially (or even completely) offset by his strong points. For example, a nongraduate, 17-year-old applicant with a low GCT (say 70) and a CI score of 120 has a probability of attrition of approximately 41 percent. Depending on the prevailing recruiting standards and quotas, this applicant may be rejected (denied enlistment) because of his low GCT. On the other hand, a similar applicant with a GCT of 110 and a CI of 60 may be accepted because of his relatively high GCT. This second applicant, however, has approximately the same probability of attrition as the first and should, therefore, have the same chance of acceptance. While such a large GCT-CI divergence is unlikely, it is the principle that should be considered, not the exact numbers. The fact is that tradeoffs among enlistment screening variables is possible when a CAREM-type regression model is used. Figure 4 illustrates the GCT-CI tradeoffs for nongraduates, ages 17 to 20, for two values of predicted attrition.

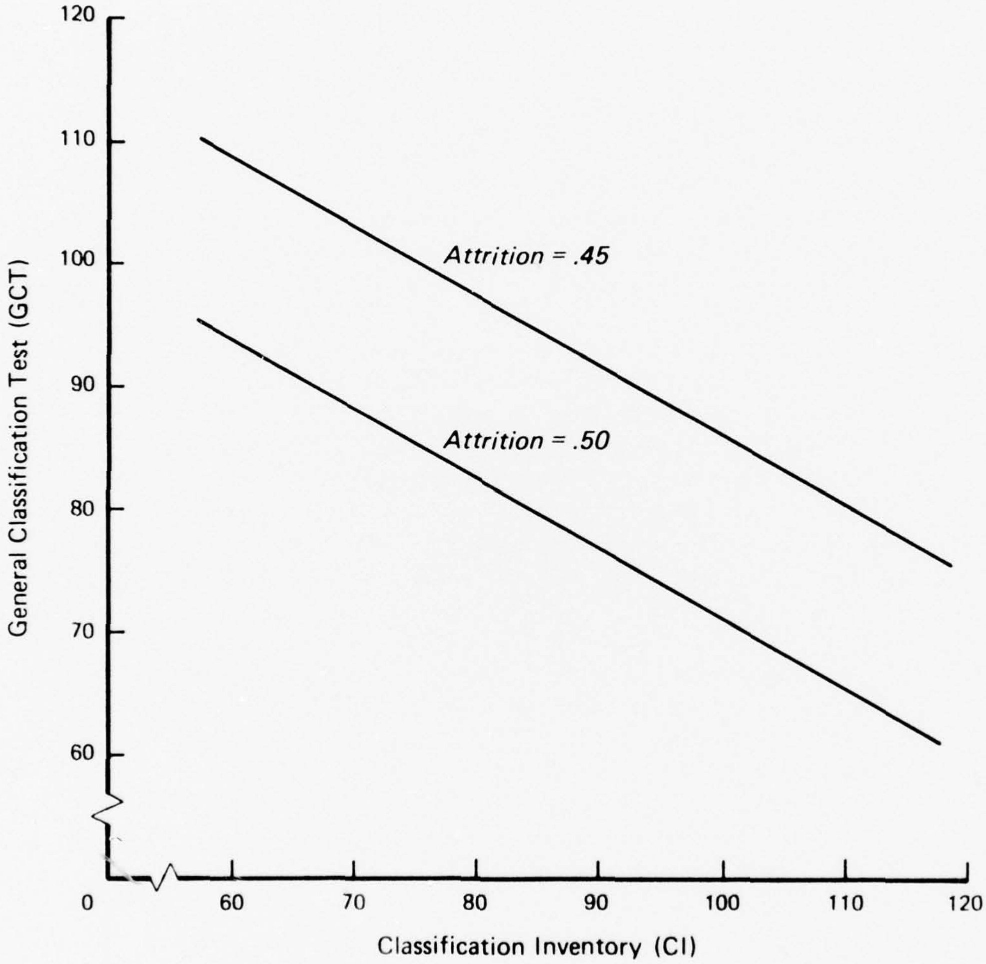

FIG. 4: GCT-CI TRADE OFFS FOR EQUAL ATTRITION (NONGRADUATES, AGED 17 TO 20)

Allowing such tradeoffs among the variables has the distinct advantage of enlarging the size of the eligible population by making persons eligible who otherwise would not be. In a recruiting environment where recruit demand exceeds supply, such a step should be seriously considered.

Concerning the general applicability of the methodology: There appears to be a danger in sanguinely accepting the results of comparisons based on F and Chi-square tests. The results of such tests should be examined carefully for their applicability and checked, if possible, in a practical application of the models being compared. Only then can one derive a clear understanding of the nature of the forecasts being made.

REFERENCES

1. Center for Naval Analyses, Study 1100, "Quality of Marines: Test Scores, Personal Data, and Performance," by Warren T. Matthews, Unclassified, forthcoming

2. Center for Naval Analyses, Research Contribution 326, "Profile of a Successful Marine," by William H. Sims, Unclassified, forthcoming

3. Headquarters, Fleet Marine Force, Atlantic, "Fleet Marine Force, Atlantic Enlisted Personnel Study," Unclassified, Aug 1975

4. Center for Naval Analyses, Study 1084, "An Analysis of Marine Corps School Assignment and Performance," by Steve Verna and Thomas L. Mifflin, Unclassified, forthcoming

5. Journal of the American Statistical Association, Volume 63, "A Test of the Mean Square Error Criterion for Restrictions in Linear Regression," Unclassified, pp. 558-572, 1968

6. Center for Naval Analyses, Professional Paper 177, "Predicting Attrition: A Test of Alternative Approaches," by Robert F. Lockman and John T. Warner, Unclassified, Mar 1977

APPENDIX A

MEANS, STANDARD DEVIATIONS, CONFIDENCE INTERVALS, AND CORRELATION COEFFICIENTS

APPENDIX A

MEANS, STANDARD DEVIATIONS, CONFIDENCE INTERVALS, AND CORRELATION COEFFICIENTS

This appendix contains tables that display the means, standard deviations, and confidence intervals for observed values of the dependent and independent variables. It also contains tables that show the coefficients of correlation between all possible pairs of variables. The column and row abbreviations are as follows:

Abbreviation	Variable
VATTR	Attrition and/or desertion during first 2 years
AGE 21	Age at enlistment (17-20 or over 21)
RACE	Race (white or nonwhite)
MARIT	Marital status at enlistment (married or unmarried)
GUAR	Enlistment guarantee (none, cash, or noncash)
MCRD	Marine Corps Recruit Depot (This variable was in the data base and therefore appears in the table; however it was not used in the analysis.)
	ACB-61 subtests:
VE	Verbal
AR	Arithmetic
PA	Pattern Analysis
CI	Classification Inventory
MA	Mechanical Aptitude
ACS	Army Coding Speed
ARC	Army Radio Code
GIT	General Information
SM	Shop Information
AI	Automotive Information
ELI	Electronics Information
GCT	General Classification Test

TABLE A-1

HIGH SCHOOL GRADUATE MEANS, STANDARD DEVIATIONS, AND CONFIDENCE INTERVALS

Variable	Mean	Standard deviation	95-percent confidence interval[a]
Attrition	0.2029	0.4022	0.1976 - 0.2082
Age	0.1249	0.3307	0.1206 - 0.1292
Race	1.2045	0.4034	1.1992 - 1.2096
Marital status	1.0647	0.2532	1.0614 - 1.0680
Enlistment guarantee	0.6391	0.5825	0.6315 - 0.6467
ACB-61 scores:			
VE	108.24	22.22	107.9487 - 108.5313
AR	103.43	22.26	103.1382 - 103.7218
PA	110.96	21.48	110.6784 - 111.2416
CI	102.49	26.45	102.1433 - 102.8367
MA	104.34	20.16	104.0757 - 104.6043
ACS	103.00	19.76	102.7410 - 103.2590
ARC	90.06	26.50	89.7126 - 90.4074
GIT	99.41	19.84	99.1499 - 99.6701
SM	101.10	18.90	100.8524 - 101.3478
AI	102.46	19.53	102.2040 - 102.7160
ELI	97.47	23.92	97.1564 - 97.7836
GCT	107.54	19.56	107.2836 - 107.7964

[a]The precise meaning of a confidence interval for a dichotomous variable is unclear. Values are shown primarily for convenience and consistency.

TABLE A-2

NONGRADUATE MEANS, STANDARD DEVIATIONS, AND CONFIDENCE INTERVALS

Variables	Mean	Standard deviation	95-percent confidence interval
Attrition	0.4469	0.4972	0.4406 - 0.4532
Age	0.0781	0.2683	0.0742 - 0.0815
Race	1.2437	0.4293	1.2382 - 1.2492
Marital status	1.0763	0.2738	1.0728 - 1.0798
Enlistment guarantee	0.4310	0.4965	0.4275 - 0.4373
ACB-61 scores:			
VE	92.62	20.98	92.5373 - 92.7027
AR	88.63	19.96	88.3755 - 88.8847
PA	100.38	22.00	100.0993 - 100.6607
CI	89.99	27.23	89.6425 - 90.3375
MA	94.56	18.21	94.3276 - 94.7924
ACS	92.47	19.49	92.2213 - 92.7187
ARC	77.89	23.80	77.5863 - 78.1937
GIT	87.43	18.52	87.1937 - 87.6663
SM	91.67	17.97	91.4407 - 91.8993
AI	95.75	18.46	95.5144 - 95.9856
ELI	88.07	22.45	87.7835 - 88.3565
GCT	93.88	18.05	93.6497 - 94.1103

TABLE A-3

HIGH SCHOOL GRADUATE CORRELATION COEFFICIENTS

	RACE	MARIT	VE	AR	PA	CI	MA	ACS	ARC
RACE	1.00000	0.02011	-0.42499	-0.41910	-0.39981	-0.29453	-0.42294	-0.33019	-0.29928
MARIT	0.02011	1.00000	-0.01710	-0.00712	-0.01434	0.00931	-0.00514	-0.02102	-0.01248
VE	-0.42499	-0.01710	1.00000	0.74115	0.62665	0.55289	0.65066	0.53167	0.49693
AR	-0.41910	-0.00712	0.74115	1.00000	0.69150	0.49631	0.64123	0.62006	0.52804
PA	-0.39981	-0.01434	0.62665	0.69150	1.00000	0.45826	0.64709	0.57268	0.48483
CI	-0.29453	0.00931	0.55289	0.49631	0.45826	1.00000	0.52660	0.43930	0.37548
MA	-0.42294	-0.00514	0.65066	0.64123	0.64709	0.52660	1.00000	0.54557	0.46101
ACS	-0.33019	-0.02102	0.53167	0.62006	0.57268	0.43930	0.54557	1.00000	0.52767
ARC	-0.29928	-0.01248	0.49693	0.52804	0.48483	0.37548	0.46101	0.52767	1.00000
GIT	-0.48949	-0.00371	0.74329	0.65727	0.60634	0.54605	0.66500	0.50517	0.44635
SM	-0.42643	0.00095	0.63009	0.59762	0.62162	0.48363	0.69742	0.49471	0.40201
AI	-0.39549	0.04087	0.48753	0.47765	0.52142	0.40903	0.61061	0.37001	0.28757
ELI	-0.34326	0.00332	0.57294	0.54375	0.57439	0.39783	0.60181	0.38194	0.32429
MCRD	-0.13362	0.00225	0.08133	0.07777	0.07488	0.15990	0.06861	-0.03043	0.05934
GUAR	-0.23034	0.00628	0.28316	0.28533	0.27296	0.21234	0.25321	0.18956	0.17501
AGE21	0.10919	0.21702	-0.00112	-0.01431	-0.06517	0.00743	-0.04278	-0.06033	-0.03240
VATTR	0.09532	0.03896	-0.14508	-0.16778	-0.17644	-0.16967	-0.15504	-0.14011	-0.12869
GCT	-0.46627	-0.01442	0.88922	0.91313	0.86567	0.56539	0.72651	0.64618	0.56596

TABLE A-3 (CONT'D)

HIGH SCHOOL GRADUATE CORRELATION COEFFICIENTS

	GIT	SM	AI	ELI	MCRD	GUAR	AGE21	VATTR	GCT
RACE	-0.46949	-0.42643	-0.39549	-0.34326	-0.13362	-0.23034	0.10919	0.09532	-0.46627
MARIT	-0.00371	0.00095	0.04087	0.00332	0.00225	0.00628	0.21702	0.03896	-0.01442
VE	0.74329	0.63009	0.48753	0.57294	0.08133	0.28316	-0.00112	-0.14508	0.88922
AR	0.65727	0.59762	0.47765	0.54375	0.07777	0.28533	-0.01431	-0.16778	0.91313
PA	0.60634	0.62162	0.52142	0.57439	0.07488	0.27296	-0.06517	-0.17644	0.86567
CI	0.54605	0.48363	0.40903	0.39783	0.15990	0.21234	0.00743	-0.16967	0.56539
MA	0.66500	0.69742	0.61061	0.60181	0.06861	0.25321	-0.04278	-0.15504	0.72651
ACS	0.50517	0.49471	0.37001	0.38194	-0.03043	0.18956	-0.06033	-0.14011	0.64618
ARC	0.44635	0.40201	0.28757	0.32429	0.05934	0.17501	-0.03240	-0.12869	0.56596
GIT	1.00000	0.70967	0.63939	0.62146	0.15077	0.27210	0.00823	-0.17123	0.75276
SM	0.70967	1.00000	0.71342	0.63681	0.07498	0.25725	-0.03007	-0.15272	0.69285
AI	0.63939	0.71342	1.00000	0.61691	0.14774	0.21806	-0.00074	-0.12564	0.55668
ELI	0.62146	0.63681	0.61691	1.00000	0.03935	0.24728	0.00179	-0.11974	0.63349
MCRD	0.15077	0.07498	0.14774	0.03935	1.00000	0.05253	0.00135	-0.10753	0.08771
GUAR	0.27210	0.25725	0.21806	0.24728	0.05253	1.00000	-0.06465	-0.12329	0.31538
AGE21	0.00823	-0.03007	-0.00074	0.00179	0.00135	-0.06465	1.00000	0.11318	-0.02971
VATTR	-0.17123	-0.15272	-0.12564	-0.11974	-0.10753	-0.12329	0.11318	1.00000	-0.18317
GCT	0.75276	0.69285	0.55668	0.63349	0.08771	0.31538	-0.02971	-0.18317	1.00000

TABLE A-4

NONGRADUATE CORRELATION COEFFICIENTS

	RACE	MARIT	VE	AR	PA	CI	MA	ACS	ARC
RACE	1.00000	-0.03634	-0.31169	-0.29590	-0.30296	-0.22057	-0.34195	-0.25716	-0.21488
MARIT	-0.03634	1.00000	-0.02393	-0.01565	-0.00244	0.00448	0.00047	0.00578	0.00160
VE	-0.31169	-0.02393	1.00000	0.66821	0.55290	0.55567	0.60707	0.47285	0.44336
AR	-0.29590	-0.01565	0.66821	1.00000	0.61457	0.46697	0.55730	0.54249	0.45405
PA	-0.30296	-0.00244	0.55290	0.61457	1.00000	0.41721	0.54292	0.52893	0.43114
CI	-0.22057	0.00448	0.55567	0.46697	0.41721	1.00000	0.51587	0.42630	0.34870
MA	-0.34195	0.00047	0.60707	0.55730	0.54292	0.51587	1.00000	0.52361	0.40829
ACS	-0.25716	0.00578	0.47285	0.54249	0.52893	0.42630	0.52361	1.00000	0.47854
ARC	-0.21488	0.00160	0.44336	0.45405	0.43114	0.34870	0.40829	0.47854	1.00000
GIT	-0.37263	0.01369	0.70903	0.59548	0.52712	0.53565	0.62358	0.46236	0.39960
SM	-0.36215	0.00904	0.63279	0.55984	0.54495	0.50244	0.67856	0.49498	0.38341
AI	-0.37808	0.05653	0.53783	0.49057	0.49190	0.42916	0.61687	0.40501	0.29925
ELI	-0.25843	0.01681	0.52838	0.46509	0.49663	0.35745	0.50532	0.34383	0.28680
MCRD	-0.17948	-0.00317	0.17175	0.13435	0.11823	0.27331	0.11675	0.02542	0.06670
GUAR	-0.20935	-0.00827	0.32526	0.31661	0.28077	0.22125	0.27498	0.21118	0.19991
AGE21	0.08148	0.24255	-0.02496	-0.03092	-0.06901	-0.00477	-0.03738	-0.05327	-0.04138
VATTR	0.05542	0.02766	-0.14527	-0.15927	-0.16990	-0.17325	-0.12932	-0.11837	-0.10970
GCT	-0.35292	-0.01604	0.85838	0.87717	0.84700	0.55692	0.66120	0.59805	0.51430

TABLE A-4 (CONT'D)

NONGRADUATE CORRELATION COEFFICIENTS

	GIT	SM	AI	ELI	MCRD	GUAR	AGE21	VATTR	GCT
RACE	-0.37263	-0.36215	-0.37808	-0.25843	-0.17948	-0.20935	0.08148	0.05542	-0.35292
MARIT	0.01369	0.00904	0.05653	0.01681	-0.00317	-0.00827	0.24255	0.02766	-0.01604
VE	0.70903	0.63279	0.53783	0.52838	0.17175	0.32526	-0.02496	-0.14527	0.85838
AR	0.59548	0.55984	0.49067	0.46509	0.13435	0.31661	-0.03092	-0.15927	0.87717
PA	0.52712	0.54495	0.49190	0.49663	0.11823	0.28077	-0.06901	-0.16990	0.84700
CI	0.53565	0.50244	0.42916	0.35745	0.27331	0.22125	-0.00477	-0.17325	0.55692
MA	0.62358	0.67856	0.61687	0.50532	0.11675	0.27498	-0.03738	-0.12932	0.66120
ACS	0.46236	0.49498	0.40501	0.34383	0.02542	0.21118	-0.05327	-0.11837	0.59805
ARC	0.39960	0.38341	0.29925	0.28680	0.08670	0.19991	-0.04138	-0.10970	0.51430
GIT	1.00000	0.67760	0.66002	0.56338	0.25803	0.29553	0.01118	-0.15749	0.70835
SM	0.67760	1.00000	0.71413	0.56524	0.14475	0.27473	-0.02284	-0.14264	0.67292
AI	0.66002	0.71413	1.00000	0.58750	0.18071	0.25834	0.02776	-0.12182	0.58908
ELI	0.56338	0.56524	0.58750	1.00000	0.08808	0.24150	0.00317	-0.10822	0.57791
MCRD	0.25803	0.14475	0.18071	0.08808	1.00000	0.09493	-0.01522	-0.16338	0.16410
GUAR	0.29553	0.27473	0.25834	0.24150	0.09493	1.00000	-0.04497	-0.10682	0.35679
AGE21	0.01118	-0.02284	0.02776	0.00317	-0.01522	-0.04497	1.00000	0.04512	-0.04910
VATTR	-0.15749	-0.14264	-0.12182	-0.10822	-0.16338	-0.10682	0.04512	1.00000	-0.18401
GCT	0.70835	0.67292	0.58908	0.57791	0.16410	0.35679	-0.04910	-0.18401	1.00000

APPENDIX B

REGRESSION RESULTS

APPENDIX B

REGRESSION RESULTS

This appendix contains the results of ten separate regressions: one for each of five combinations of variables for both high school graduates and nongraduates. The tables show the successive values of the R^2 and F statistics, the cumulative R^2 values, the regression coefficients for each variable, and the regression constants. The constants appear as the first entry in the "coefficient" column opposite the regression number.

TABLE B-1

REGRESSION RESULTS: HIGH SCHOOL GRADUATES

Regression number	Variables	ΔR^2	Cumulative R^2	Coefficient	F
HS-1				0.6633	
	PA	0.03113	0.03113	-0.0013	42.6
	AGE	0.01038	0.04151	0.1256	234.5
	CI	0.01088	0.05239	-0.0014	121.2
	GUAR	0.00393	0.05632	-0.0437	84.3
	GIT	0.00200	0.05832	-0.0017	49.1
	VE	0.00053	0.05885	0.0011	26.4
	AR	0.00094	0.05980	-0.0009	17.9
	RACE	0.00041	0.06020	-0.0251	10.7
	ARC	0.00043	0.06063	-0.0004	8.4
	MARIT	0.00029	0.06092	0.0277	6.8
	ELI	0.00017	0.06109	0.0004	4.8
	SM	0.00005	0.06114	-0.0002	0.9
	ACS	0.00000	0.06115	0.0000	0.0
	AI	0.00000	0.06115	0.0000	0.0
	MA	0.00000	0.06115	0.0000	0.0
HS-2				0.6150	
	GCT	0.03355	0.03355	-0.0025	241.3
	AGE	0.01162	0.04517	0.1341	286.3
	CI	0.00695	0.05212	-0.0015	163.8
HS-3				0.6774	
	PA	0.03113	0.03113	-0.0015	62.9
	CI	0.00998	0.04111	-0.0014	117.2
	GIT	0.00215	0.04326	-0.0015	38.8
	ARC	0.00054	0.04380	-0.0004	8.1
	VE	0.00061	0.04441	0.0011	25.3
	AR	0.00082	0.04523	-0.0009	16.8
	ELI	0.00016	0.04539	0.0003	4.3
	SM	0.00011	0.04550	-0.0004	2.2
	ACS	0.00002	0.04552	-0.0001	0.4
	AI	0.00001	0.04553	0.0001	0.3
	MA	0.00000	0.04553	-0.0001	0.1
HS-4				0.6190	
	GCT	0.03355	0.03355	-0.0022	175.9
	CI	0.00642	0.03997	-0.0014	139.4
	GUAR	0.00431	0.04428	-0.0478	100.7
HS-5				0.0606	
	AGE	0.01281	0.01281	0.1224	217.7
	RACE	0.00697	0.01977	0.0838	159.1
	MARIT	0.00023	0.02000	0.0245	5.2

TABLE B-2

REGRESSION RESULTS: NONGRADUATES

Regression number	Variables	ΔR^2	Cumulative R^2	Coefficient	F
NG-1				0.9510	
	CI	0.03002	0.03002	-0.0020	171.7
	PA	0.01154	0.04155	-0.0020	95.3
	GUAR	0.00235	0.04391	-0.0463	45.4
	AGE	0.00123	0.04513	0.0642	27.3
	GIT	0.00105	0.04618	-0.0015	26.6
	RACE	0.00061	0.04679	-0.0299	13.2
	AR	0.00053	0.04732	-0.0011	19.6
	VE	0.00034	0.04766	0.0007	8.1
	MARIT	0.00034	0.04800	0.0345	8.3
	MA	0.00025	0.04825	0.0007	6.8
	SM	0.00009	0.04834	-0.0005	2.6
	ARC	0.00009	0.04843	-0.0003	2.8
	ACS	0.00007	0.04850	0.0003	2.0
	ELI	0.00006	0.04856	0.0002	1.5
	AI	0.00000	0.04856	0.0000	0.0
NG-2				0.9333	
	GCT	0.03386	0.03386	-0.0034	261.7
	CI	0.00726	0.04112	-0.0019	183.2
	AGE	0.00248	0.04360	0.0714	36.4
NG-3				0.9517	
	CI	0.03002	0.03002	-0.0020	172.5
	PA	0.01154	0.04155	-0.0021	106.0
	AR	0.00145	0.04301	-0.0012	24.6
	GIT	0.00068	0.04369	-0.0014	22.6
	MA	0.00032	0.04401	0.0007	5.8
	VE	0.00015	0.04415	0.0005	4.5
	ARC	0.00010	0.04425	-0.0003	3.0
	ACS	0.00007	0.04432	0.0003	2.2
	SM	0.00007	0.04439	-0.0005	2.8
	ELI	0.00006	0.04446	0.0002	1.2
	AI	0.00002	0.04447	0.0002	0.5
NG-4				0.9213	
	GCT	0.03386	0.03386	-0.0031	194.8
	CI	0.00726	0.04112	-0.0019	173.8
	GUAR	0.00173	0.04285	-0.0446	42.7
NG-5				0.3241	
	RACE	0.00307	0.00307	0.0617	66.6
	AGE	0.00166	0.00473	0.0662	28.2
	MARIT	0.00041	0.00514	0.0380	9.8

APPENDIX C

CHI-SQUARE TEST FOR CONSISTENCY/INDEPENDENCE

APPENDIX C

CHI-SQUARE TEST FOR CONSISTENCY/INDEPENDENCE

Suppose a sample of size N is grouped according to two characteristics (A and B) as follows:

	Characteristic B						
Characteristic A	1	2	.	.	.	k	
1	f_{11}	f_{12}	.	.	.	f_{1k}	m_1
2	f_{21}	f_{22}	.	.	.	f_{2k}	m_2
3	f_{31}	f_{32}	.	.	.	f_{3k}	m_3
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
r	f_{r1}	f_{r2}	.	.	.	f_{rk}	m_r
	n_1	n_2	.	.	.	n_k	N

where f_{ij} = the number of sample members (frequency) in the cell in the i^{th} row and j^{th} column,

$$n_j = \sum_{i=1}^{r} f_{ij},$$

$$m_i = \sum_{j=1}^{k} f_{ij},$$

and $$N = \sum_{i=1}^{r} m_1 = \sum_{j=1}^{k} n_j .$$

If the two characteristics are independent, the expected number of sample members in any cell ij (i.e., the expected frequency) is given by:

$$e_{ij} = \frac{m_i n_j}{N} \quad . \tag{C-1}$$

The observed frequency is given simply by:

$$o_{ij} = f_{ij} \quad . \tag{C-2}$$

The standard expression for the Chi-square statistic is:

$$\chi^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i} \quad , \tag{C-3}$$

where o_i and e_i are the observed and expected frequencies of k possible events. This statement (i.e., C-3) is equivalent to:

$$\chi^2 = \sum_{i=1}^{k} \frac{o_i^2 - 2o_i e_i + e_i^2}{e_i}$$

$$\chi^2 = \sum_{i=1}^{k} \left(\frac{o_i^2}{e_i} - 2o_i + e_i \right)$$

$$\chi^2 = \sum_{i=1}^{k} \frac{o_i^2}{e_i} - 2 \sum_{i=1}^{k} o_i + \sum_{i=1}^{k} e_i$$

$$\chi^2 = \sum_{i=1}^{k} \frac{o_i^2}{e_i} - 2N + N \tag{C-4}$$

$$\chi^2 = \sum_{i=1}^{k} \frac{o_i^2}{e_i} - N.$$

Substituting from equations C-1 and C-2 above, we now have:

$$\chi^2 = \sum_{i,j=1}^{rk} \frac{f_{ij}^2}{m_i n_j / N} - N$$

and

$$\chi^2 = N \left(\sum_{i,j=1}^{rk} \frac{f_{ij}^2}{m_i n_j} - 1 \right) . \qquad \text{(C-5)}$$

The characteristics used in this test need not be numerical groupings. They may be such things as: pass, fail, good, average, poor, correct, incorrect, and the like. For the Chi-square test used in this analysis, characteristic A indicates the performance of the model (correct acceptance, etc.), while characteristic B indicates the choice of models. Thus, the contingency table for the CAREM = 0.50 Chi-square calculation is:

Characteristic A	Characteristic B: Aggregated	Characteristic B: Disaggregated	
Correct acceptances	27,422	27,342	54,764
Incorrect acceptances	11,651	11,525	23,176
Correct rejections	4,026	4,152	8,178
Incorrect rejections	2,986	3,066	6,052
	46,085	46,085	92,170

which, using equation C-5, leads to a Chi-square value of 3.80.

Recall that during the derivation of the Chi-square formula, an assumption was made that "...*if the two characteristics are independent*...." The results may now be used to test that assumption. The null hypothesis for the test is that characteristic A is independent of characteristic B--i.e., that the numbers of correct acceptances, etc., are independent of the choice of the model. If the calculated value of the Chi-square statistic (equation C-5) exceeds some specified critical value (from standard Chi-square tables), then the null hypothesis may be rejected. The conclusion then would be that the models are different. In the case of the models examined in this analysis, the ability to reject the null hypothesis appears to be dependent upon the choice of the CAREM cutting score, as previously reported.